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Quality and Consumer Choice in Healthcare: Evidence from Kidney Transplantation

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Abstract: Most studies of competition in health care focus on prices and costs, but concerns about quality play a central role in policy debates. If demand is inelastic to quality, then competition may reduce patient welfare. This study uses a dataset of patient registrations for kidney transplantation in conjunction with a mixed logit model to gauge consumers' responsiveness to quality when choosing hospitals. Results indicate that a one-standard deviation increase in graft-failure rates leads to a 2 to 5 percent decline in patient demand. Privately-insured patients are more responsive to quality than government-insured patients, suggesting that insurers consider quality when contracting with providers.

The data reported here have been supplied by the University Renal Research and Education Association as the contractor for the Scientific Registry of Transplant Recipients (SRTR). The interpretation and reporting of these data are the responsibility of the author and in no way should be seen as an official policy of or interpretation by the SRTR or the U.S. Government.

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1. Introduction

Restrictions on competition in health care markets are usually justified in terms of their ability to enhance quality and patient welfare. Faced with rising costs, however, states, courts, and the federal government have gradually repealed laws and regulations that limit providers' exposure to competitive pressures. While reforms have led to lower prices (Cutler et al. 2000; Dranove et al. 1993), the impact of competition on quality is unclear. A necessary condition for competition to promote quality in health care is that patients (and their referring physicians and health plans) take quality into account when choosing providers (Ginsburg and Hammons 1998; Dranove and Satterthwaite 1992).[1] If so, then providers with above-average quality will attract more patients.

Subjecting the assumption underlying pro-competitive policies in healthcare – that patients, if given a choice and information, will gravitate towards high-quality providers – to empirical validation is important for understanding consumer behavior and assessing public policies in the area of quality improvement. This study was undertaken to examine the responsiveness of consumers' choice of kidney transplant center to quality using a unique dataset consisting of the universe of registrants for kidney transplantation. Results from the baseline model indicate that an increase in graft failure rates of one standard deviation leads to a 5 percent decline in patient demand

Studies have analyzed consumers' responsiveness to quality in health care previously (these are reviewed below), but this is the first to examine patient choice in the field of organ transplantation. Quality is relatively easy to measure in transplantation and

[1] This is not a sufficient condition, however, in cases where sicker, high-cost patients are differentially attracted to high-quality providers (Frank et al. 2000).

hospital-specific outcomes data have been reported on the Internet since late 1999,[2] making transplantation a good case study for evaluating consumer behavior with respect to quality. While the goal of this study is to draw conclusions that apply to the health system generally, transplantation is an area of particular concern to the government given its regulatory oversight of the organ allocation system and Medicare's end-stage renal disease program, which provides insurance coverage to many patients with kidney failure.

2. Patient Choice in Health Care

Traditionally, the health care system was governed by a paternalistic mindset based on the assumption that consumers lacked or were unable to use information to select providers based on quality (Arrow 1963). Under this condition, increased competition may lead firms to compete on price at the expense of quality and reduce consumer surplus (Dranove and Satterthwaite 1992; Hart et al. 1997). Competition between providers of medical services characterized by a positive relationship between procedure volume and outcomes may be particularly detrimental to quality when consumers are misinformed. In such cases, entry lowers average volume and diminishes outcomes across the board.[3] If consumers do not consider outcomes when choosing providers, entry may be excessive and the number of firms in equilibrium will exceed the social optimally level.

[2] See http://www.ustransplant.org.
[3] Previous work has emphasized that volume-outcome effects may act as a barrier to entry (Dafny 2003), but this will only be the case if consumers consider outcomes when choosing providers.

Though the rapid pace of technological change in medicine makes it ever more difficult for laypersons to evaluate quality, a number of customs and institutions have developed over the years to mitigate consumer ignorance. As in other markets, consumers can infer quality from firms' reputations. The growth of multiplant providers has increased the returns to reputation, and some health care providers now employ strategies based on "branding" their name. Increasingly, data on the technical quality of health care are available directly to consumers. Governments, employers, and health plans have attempted to disseminate these data in the form of "report cards" listing side-by-side performance measures for providers. Report cards exist for nursing homes, health plans, and some types of surgeries. Reports cards have spurred efforts to improve quality at providers with poor outcomes (Chassin 2001), but insufficient adjustment of outcome measures for patient characteristics may lead providers to shun high-risk patients (Dranove et al. 2003).

Physicians and health plans exert a strong influence on consumers' choices and may increase the responsiveness of demand to quality. Consumers rarely choose specialists and hospitals without some type of referral from their primary care physician, who presumably is in a better position than they to judge health care quality. If physicians place value on patient welfare, then their referral patterns will reflect perceived differences in patient outcomes. Health plans influence patient flows through their use of exclusive provider networks. Though these networks are established principally to extract price discounts, plans may exclude from networks providers that perform poorly on quality measures

3. Literature Review

A number of studies have measured the responsiveness of patients to quality using individual-level choice data. Typically, consumer utility from a particular provider is modeled as a linear function of provider characteristics, and parameters estimated using a multinomial model such as a conditional logit. The advantage of this approach is that it infers the importance of quality from actual, observed behavior rather than asking patients to consider hypothetical tradeoffs between quality and other attributes. The downside is that models can incorporate only those aspects of quality that can be measured and objectively ranked. In practice, many of the studies reviewed below use quality measures such as teaching status or in-hospital mortality that may be weak indicators of patients' expected utility.

In one of the earliest studies using this approach, Luft et al. (1990) examined the impact of direct measures of quality, including death and complication rates, and indirect measures of quality, including teaching status and percent of number of out-of-state admissions, on patients' choice of hospital in California for seven categories of admissions. For all admission categories examined, indirect measures of quality increased the likelihood of being chosen, but the direct measures of quality were only significant in the expected direction for five of the seven admission categories. Quality measures appeared to have a greater impact on surgical admissions than medical admissions. Demand elasticities for quality were fairly small for most procedures. However, the measures of direct quality – in-hospital mortality and complications rates – may be weak signals of actual quality since hospitals that discharge patients early will tend to have lower rates of in-hospital adverse events.

Burns and Wholey (1992) replicated the study of Luft et al. using discharge data from Arizona with measures of physician referral patterns. They found that referral patterns have a strong impact on choice but do not diminish the impact of quality measures. Several studies have provided additional evidence that patients' choices are responsive to quality, as measured by teaching status, service availability, and capital expenditures (Adams et al.1991; Capps et al. 2001; Chirikos 1992; Dranove and White 1993).

Disease-specific studies have focused on factors affecting demand for hospitals' obstetric and cardiac services. Brounstein and Morrisey (1991) examined the decision to bypass the closest hospital for women giving birth in Alabama in 1983 and 1988. Bed size and presence of specialized birth services did not influence the travel decision, but lagged volume, which has been shown in the clinical research to be a predictor of a hospital's birth outcomes, was strongly related to hospital choice. Upper income women and white women were significantly more likely to bypass the closest hospital and travel to a metropolitan hospital with strong quality indicators.

Phibbs et al. (1993) examined the choice of hospital for delivery by women in the San Francisco Bay Area. They found that quality, as measured by hospitals' risk-adjusted perinatal mortality, influenced hospital choice, as did a number of proxies for quality, including teaching status, ownership, and the presence of a neonatal intensive care unit. Women with potential high-risk pregnancies were more responsive to quality measures than women with routine deliveries and, somewhat surprisingly, Medicaid recipients were more responsive to quality than privately insured patients, though it is difficult to tell whether this finding reflects patient preferences or selective contracting arrangements by insurers.

Hodgkin (1996) used discharge data from New Hampshire to examine the impact of hospitals' adoption of cardiac catheterization technology on demand. Unlike past studies, Hodkin allowed for hospital fixed effects. He found that opening a catheterization laboratory increased demand among patients likely to use the service, but had no impact for other types of patients, refuting the hypothesis that offering high-tech services is a way for hospitals to signal quality.

Tay (2002) estimated the tradeoff between heart attack patients' travel distance and hospital quality, as measured by presence of a catheterization laboratory, staffing ratios, and mortality rates. She found that all measures of quality were correlated with patients' choice of hospital. Simulations showed that hospitals experience significant increases in patient demand after opening catheterization laboratories or increasing staffing per bed ratios.

Overall, studies of consumer choice in health care find that patients are more likely to choose providers with higher quality levels, all else being equal. In most of the cases considered, hospital quality measures were not publicly reported, suggesting that at least some patients are well-informed even in the absence of "report card" programs. Unfortunately, these studies do not answer the question "How responsive to quality must consumer choice be in order to guarantee that competition produces socially desirable outcomes?" The magnitude of the effect remains in the eye of the beholder.

4. Background on Kidney Transplantation

In 2001, 26,882 kidney transplants were performed at over 230 hospitals. About one half of transplant recipients receive a kidney from a living donor, usually a friend or family member. Candidates who cannot obtain a living donor kidney are placed on the waiting list to await a kidney from a deceased. The waiting list is national in scope, though patients in the region in which an organ was recovered are given preference over others, giving rise to regional disparities in waiting times. Over 22,000 patients are placed on the waiting list annually, and at the end of 2001, there were 51,144 patients waiting for a donor, including those listed in prior years.

Entry of hospitals into transplantation is regulated by states and the federal government. Some physicians, citing studies on the volume-outcome relationship in transplantation, have argued that transplant services ought to be restricted to a handful of high-volume centers in each region. Although regulators are sympathetic to these concerns, entry restrictions have been relaxed in recent years and hospitals, attracted by profits and the perceived prestige of transplantation, have continued to open new centers.[4] Most major cities now have at least two kidney transplant centers and, though the majority of procedures continue to be performed at large academic medical centers, kidney transplantation is increasingly viewed as a "routine" medical procedure on par with other major surgeries.

Center-specific patient outcomes data have been reported publicly since 1992. Prior to September of 1999, actual and expected (i.e. case-mix adjusted) survival rates for

[4] For models of entry in transplantation, see Barnett and Kaserman 1995 and Possai and Goetz 1994.

every transplant center were listed in hardcopy reports. Their value to patients was limited; the reports were available only at medical libraries and government depositories and the data used to construct the survival rates were several years out of date by the time the reports were released. At the behest of the federal government, center-specific survival reports were placed on the Internet beginning in September of 1999 and updated more frequently.

Patients deemed suitable candidates for transplantation typically choose transplant centers shortly after diagnosis, in consultation with their nephrologist. Undoubtedly the nephrologist's recommendation holds sway for many patients, but nephrologists do not exert formal authority over patients' choices, and patients are free to disregard their advice. From the patient's perspective, transplant centers are differentiated by the travel time from the patient's home to the center and quality. Almost all transplant operations are covered by insurance, so price is not a factor. Candidates for cadaveric transplants who live near regional boundaries may consider expected waiting times when choosing a transplant center, but most face little variation between nearby centers. About 5 percent of patients register at more than one transplant center – usually one local center and one out-of-region center – to increase their chances of obtaining a kidney. After the first registration, patients must pay registration fees out-of-pocket, and so this strategy is available only to upper income patients.

Patients' choices are constrained by their insurers. Medicare covers transplantation at any center meeting a fairly minimal set of criteria in terms of staffing and procedure volume, but state-run Medicaid programs cover kidney transplantation at in-state facilities only. Private insurers bargain aggressively with transplant programs, and most restrict coverage to a few centers in each geographic area under the guise of "centers of excellence" programs. Insurers maintain that the purpose of these programs is to direct patients to hospitals with superior outcomes, but critics charge that obtaining price discounts, not improving quality, is the primary objective of exclusive networks in transplantation (Burns et al. 2000). These competing claims are assessed empirically by examining whether privately insured patients, whose choices are constrained, are more or less likely to register at centers with good outcomes than Medicare patients, whose choices are unrestricted

The rules governing insurance coverage for patients with kidney failure are complicated. All patients over the age of 65 are covered by Medicare. Very few are in Medicare managed plans. For patients under age 65, coverage depends on how long they have been diagnosed with kidney failure. Immediately following diagnosis, coverage remains unchanged for patients who had insurance prior to diagnosis. At three months post-diagnosis, Medicare becomes the "secondary payer", covering the portion of bills that are not paid by the patient's primary insurer. At 30 months post-diagnosis, Medicare assumes "primary payer" status. If patients undergo kidney transplantation within three months following diagnosis, the three month waiting period no longer applies, and Medicare becomes the secondary payer (for patients with private insurance or Medicaid) or the primary payer (for uninsured patients). Hospitals generally refuse to transplant uninsured patients out of concern that they will be unable to afford the post-transplant immunosuppressive medications necessary to maintain graft function.

5. Data and Methods

5.1 Data

The main study sample consists of adults registering for kidney transplants between January 1, 2000 and October 31, 2002. These data were obtained from the Scientific Registry of Transplant Recipients, which is located at the University of Michigan, and are compiled from forms transplant centers are required to file with the Organ Procurement and Transplantation Network (OPTN). Because registration is mandatory, the database includes the universe of candidates for deceased donor transplants in the United States. The OPTN uses the data to rank patients on the waiting list and for research purposes. The database also includes about 30 percent of living-donor transplant recipients, who are not required to register with the OPTN but may elect to do so.

The following groups of patients were excluded from the analysis: patients residing outside the continental United States, candidates for multi-organ transplants, (who must choose from a much narrower set of hospitals, those that perform liver, lung, pancreas, or intestine transplants), patients who have been transplanted previously (the vast majority of whom register at the institution where they received the first procedure), patients registering at transplant centers that were not in operation long enough to be included in the most recent center-specific survival report, patients with only one transplant center in their choice set, and patients who registered at a transplant center not included in their choice set. The final sample size is 36,678.

Choice sets – the subset of transplant centers that patients plausibly consider when choosing a transplant center – were constructed based on historical registration patterns and distance. Through trial and error, the following criteria were found to yield choice sets that include the actual choice of 96 percent of registrants as an element (the remaining 4 percent were excluded):

Include transplant center j in patient i's choice set if:

- center j was accepting registrants in the year in which patient i registered,
- at least 5% of patients from patient i's metropolitan statistical area (MSA) registering for a transplant in the previous two years choose center j, or
- if center j is less than 30 miles from patient i's home.

The first criterion incorporates actual choice patterns into the formation of choice sets, and the second allows newer centers (which may have only small market shares in previous years) to be included in the choice sets of nearby patients. Choice sets were limited to a maximum 10 transplant centers. Patients living outside of MSAs were associated with MSAs based on the first three digits of their zip code or, for patients whose first three zip code digits do not correspond to the first three digits of a zip code located in an MSA, distance.

5. 2 Variable construction

Patients, physicians, and health plans consider many different factors when choosing transplant centers. For purposes of estimating statistical choice models, it is necessary to limit the analysis to those that can be observed and measured unidimensionally. In the baseline analysis, transplant centers are characterized by three attributes: quality (i.e. patient outcomes), travel distance, and lagged market share.

Transplant center quality is measured by the difference between each centers' expected and actual graft failure rates at one-year post-transplant.[5,6] A patient is counted towards a center's graft failure rate if they die, regardless of the cause of death, or their body rejects the donor organ and they are placed on dialysis or receive a second transplant. Graft failure rates were abstracted from center-specific survival reports, provided in electronic format to the author by the United Network for Organ Sharing and the University Renal Research and Educational Association. Expected graft failure rates are calculated for each center after adjusting for a rich set of patient controls, including age, primary diagnosis, physiological measures of pre-transplant kidney function, and characteristics of the kidney donor. Taking the difference between the expected and

[5] Center-specific survival reports include three-year graft survival rates and, ideally, the choice model would include both three- and one-year graft survival rates as quality indicators, but this may be difficult because one- and three-year rates are highly collinear and three-year graft survival rates are not available for transplant centers that have been in operation for less than three years. More than one-year graft failure rates, three-year graft failure rates are determined by factors outside centers' control (for example, patient compliance with immunosuppressive medications).

[6] Previously, Luft et al. and others have measured quality by constructing a z-score, which incorporates both the differences between actual and expected mortality rates as well as the number of procedures performed by each center. The raw difference between the expected and actual rates is used here for ease of interpretation and computation of elasticities. The z-score and raw difference are highly correlated (? = 0.83).

actual graft failure rates effectively “risk adjusts” centers’ outcomes for underlying differences in patients’ characteristics.

It should be noted that the difference between expected and actual rates as provided to the author is not the only possible measure of transplant center quality or even the best measure (there are many references on the subject of how to measure provider quality; for example, see Normand et al. 1997). However, these measures are easy to obtain and are based on models that have been developed with extensive input from transplant physicians and biostatisticians.

In the baseline specification, quality is computed using outcome measures from the July 2003 report. This report reflects transplant operations performed during the time period in which patients in the sample where choosing hospitals. The data were not publicly available. A second model is estimated based on the outcome measures in the most recently-released report at the time of each patient’s registration.

Table 1 presents summary statistics for various outcome measures contained in the July 2003 report. The average graft failure rate at one-year post-transplant for transplants performed between January 1, 2000 and June 31, 2002 is 0.09 (9%). Not surprisingly, the mean difference between the expected graft failure rate and the actual graft failure rate is zero. The average number of transplants performed over the 30-month observation period is 155, with a range of 1 to 932.

In the baseline model, travel distance from patient i to hospital j is measured by the natural log of the great circle distance in miles from the center of patient i’s home zip code to the center of the zip code in which hospital j is located. Straight-line distance is highly correlated with actual travel times (Phibbs and Luft 1995). Using logged miles, as in Luft et al., places a reasonable restriction on the relationship between distance and utility assuming that a patient gives less weight to the difference in distance between hospitals located at, say, 105 and 110 miles from his home than the difference between hospitals located at 5 and 10 miles.

The relationships between nephrologists and local transplant centers influence where patients register for transplants. Lacking nephrologist-specific identifiers, lagged, city-specific market shares are used as a proxy for these relationships. Formally, the lagged market share variable for patient i and hospital j equals the proportion of patients from patient i's MSA (or, for patients living in rural areas, the MSA to which they were linked) registering at hospital j in the past two years. Table 2 displays summary statistics for the transplant center attributes. The first panel displays statistics for individuals' chosen centers, the second displays statistics for the entire dataset, which includes all centers in each patient's choice set.

Each transplant center attribute is interacted with the following patient characteristics: age (<65 versus ≥65), race/ethnicity (white versus non-white), cause of renal failure (diabetes versus other), current treatment (dialysis versus none), education (college degree versus none), and insurance type (private versus Medicaid versus other). Including three transplant center attributes as levels and interactions with eight patient characteristics generates a model with 27 (= 3 × [1 + 8]) variables.

Patient characteristics are summarized in Table 3. Racial and ethnic minorities are disproportionately represented among transplant registrants (53%). Only 15 percent of patients have a college degree, compared to 26 percent of the general adult population (U.S. Census Bureau 2001). Medicaid is the source of insurance for 7 percent of registrants, and 47 percent have private insurance. Most of the remaining 46 percent are insured by the Medicare program.

5.3 Statistical Model

Transplant center choice was modeled using a mixed logit model with an error-components specification. Mixed logit models relax the restrictive axiom of irrelevant alternatives by incorporating random terms, interacted with some or all product attributes, into the utility function, thereby allowing for correlation in the error terms across alternatives (McFadden and Train 2000). (Note that by fully interacting center attributes with patient characteristics, the model allows for additional flexibility in substitution patterns across observable patient types.)

Let z_{ij} be a vector of transplant center characteristics for center j from the perspective of patient i and w_i be a vector consisting of patient characteristics and a constant term. The vector of fully interacted center and patient attributes is $x_{ij} = (z_{ij} \otimes w_i)$. Under the mixed logit model (with error components), the utility that patient i receives from transplant center j is:

$$U_{ij} = \beta' x_{ij} + \sum_k \sigma^k \mu^k x_{ij}^k + \varepsilon_{ij} , \qquad [1]$$

where the β's and σ^k's are parameters, the μ^k's are random terms with zero mean, and the x_{ij}^k's are a subset of the terms in x_{ij}. To estimate the parameters, it is necessary to assume a distributional form for the μ^k's. A model with $\mu^k = 0$ for all k would reduce to the standard conditional logit model. In this application, the μ^k's are restricted to follow triangle distributions (see Train [2003] for a discussion of the properties of alternative distributions in mixed logit models). In this case, parameters σ describe the spread of the distributions, so that μ^k follows a triangle distribution on the interval $[-\sigma^k, \sigma^k]$.

Parameters β and σ are estimated via maximum likelihood. Assuming that ε_{ij} follows a type I extreme value distribution, the probability that patient i chooses hospital j, P_{ij}, is:

$$P_{ij} = \int_m \frac{\exp(U_{ij})}{\sum_j \exp(U_{ij})} f(m) dm . \qquad [2]$$

Monte Carlo integration is used to approximate the choice probabilities:

$$\tilde{P}_{ij} = \sum_{r=1}^{R} \frac{\exp(U_{ij}^r)}{\sum_j \exp(U_{ij}^r)} . \qquad [3]$$

where r indexes Halton draws (Train 2003) from mean-zero triangle distributions (as in Train 2002) and R is the total number of draws. Letting $y_{ij} = 1$ if patient i chose center j and zero otherwise, the simulated log-likelihood is:

$$SSL = \sum_i \sum_j y_{ij} \ln \tilde{P}_{ij} . \qquad [4]$$

Standard errors for parameters were computed using the Berndt-Hall-Hall-Hausman method. Identification of level coefficients is achieved by the variation in the attributes of hospitals within choice sets. Identification of interaction terms is achieved by the within-choice set variation and the variation in characteristics across patients.

Error components were allowed for the coefficients on the following variables: log distance, the interactions of log distance with employment status, Medicaid insurance and private insurance, lagged market share, and the interaction of lagged market share with private insurance. These variables were chosen based on prior beliefs that the influence of these characteristics on choice behavior varies in the population. Patients' ability to travel to transplant centers outside their local area varies due to differences in health status and wealth. Some but not all employed patients face vacation and sick leave policies that restrict their ability to take time off for travel to centers outside their local area. Medicaid programs generally restrict reimbursement to in-state providers; the distance between patients' homes and in-state providers will be much larger for patients who live in large states like Texas compared to patients who live in smaller states like Delaware. Some nephrologists may have strong relationships with a single transplant program, while others do not, giving rise to variation in the relationship between past referral patterns (proxied by lagged MSA-specific market share) and current referrals. The exclusivity of private insurers' provider networks varies; those with more exclusive networks will require some patients to travel outside their local areas for transplant services and have referral patterns that are more consistent over time. Error components were not placed on the quality variable and its interactions; doing so greatly complicates the computation of the choice-quality elasticities.

For this application, R was set equal to 100. The model was programmed in Matlab (The MathWorks, Inc. Matlab, Version 6. Natick, MA. 2000) and with 35,000 choosers took about 14 hours to run on a desktop computer with 456 RAM.

6. The Impact of Quality on Choice

Choice patterns were analyzed in tabular format as a preliminary analysis to the logit models. Results are displayed in Table 4. The rows of the table indicate the distance rank of a center from a patient's home. The column headings indicate the distance rank from a patient's home of the center in the patient's choice set with the highest. The numbers in the cells refer to the number and percent, respectively, of patients registering at each center by the distance rank of the highest quality center. The results show, for example, that 48 percent of patients register at the closest center when it has the best outcomes (column 1), but only 35 percent of patients register at the closest center when the second closest center has the best outcomes (column 2). Similarly, in the entire sample 3 percent of patients register at the fifth closest center (the last column), but when the fifth closest center has superior outcomes, 8 percent do (column 5). Overall, the table suggests that some patients are willing to travel longer distances to register at centers with lower post-transplant graft failure rates.

Results from the baseline mixed logit model, with the quality measure based on the July 2003 center-specific survival report, are displayed in Table 5. A log-likelihood test rejects the null hypothesis that the coefficients on the error components are equal to zero (P<0.001). Put another way, the standard conditional logit model imposes overly restrictive assumptions on choice behavior in this case.

Higher values of the quality variable indicate better patient outcomes, so a positive value on a quality coefficient indicates that patients in the group seek out high quality transplant centers. Particular groups of patients – whites, college-educated individuals, and persons with private insurance – are more likely to register at high-quality transplant centers. As a group, the coefficients on the quality measure and its interactions are jointly significant; the chi-squared statistic from a log-likelihood test of the null hypothesis that the coefficients equal zero is 294 with 9 degrees of freedom (P<0.001).

The coefficient on log distance is negative, as expected. Consistent with Medicaid policies that limit coverage to in-state facilities, the coefficient on the interaction of log distance is also negative, indicating that Medicaid patients are more likely to register at centers closer to home. The coefficient on the interaction of log distance with employment status is also negative, indicating that employed patients are less likely to register at distant centers. This result may reflect the inability of employed patients to take time off of work for travel. Lagged market share positively affects the likelihood that a center is chosen by a patient, especially for privately insured patients.

The coefficients on the error components other than the level of log distance are significantly different from zero. Taking into account all the interactions and coefficients on the error components, the mean distance parameter in the population is -0.79, with a theoretical minimum of -5.24 and maximum of 3.21. The equivalent figures for lagged market share are 3.58, -7.45, and 15.16.[7]

The individual coefficient estimates on the quality variable and its interactions are revealing, but are not particularly helpful for gauging the incentives facing providers with respect to quality. The elasticities of choice probabilities with respect to graft failure rates, which aggregate the information contained in the coefficient estimates, are more informative in this respect. Letting a equal the first nine elements of b (the coefficients on quality and its interactions) and m_j^A represent the actual graft failure rate at one year, the simulated elasticity for individual i and choice j with respect to the actual graft failure rate for j is:

$$\begin{aligned}\tilde{E}_{ij} &= \frac{\partial \tilde{P}_{ij}}{\partial m_j^A}\frac{m_j^A}{\tilde{P}_{ij}} \\ &= \frac{\partial U_{ij}}{\partial m_j^A} m_j^A \left(1-\tilde{P}_{ij}\right) \\ &= -(a'w_i) m_j^A \left(1-\tilde{P}_{ij}\right)\end{aligned} \qquad [5]$$

The simulated sample elasticity is a weighted average of the individual/choice-level elasticities,

[7] The use of mean-zero triangle distributions for the error components allows some choosers to have positive valuations of the attribute in question while others have negative valuations. Train suggests that in situations where there is a strong prior belief about tastes (for example, all choosers dislike distant transplant centers) investigators use distributions with strictly positive support. Were the purpose of this paper to estimate the distribution of tastes in the population, it would have made sense to explore alterative distributional specifications. However, since a mixed logit model was used simply to permit flexible substitution patterns, triangle distributions were chosen for reasons of computational simplicity.

$$\tilde{E} = \frac{1}{N} \sum_i \sum_j \tilde{E}_{ij} \tilde{P}_{ij} \,, \qquad [6]$$

where M is the number of choice-level observations in the dataset. The standard error of the elasticity is computed via the delta method.

The sample elasticity estimate from the baseline model (Model 1) and alternative models are displayed in Table 6. The sample elasticity with respect to the actual graft failure rate for the baseline model is -0.089 (SE 0.002), meaning that, on average, a 10 percent increase in the actual graft failure rate decreases the probability that a center will be chosen by slightly less than 1 percent. To put this result in perspective, a center that experienced an increase in its actual one-year graft failure rate of one standard deviation (0.05) from the sample average (0.09 to 0.14) could expect a 4.9 percent decline in patient registrations.

Dropping lagged market share as a center attribute (Model 2) decreases the sample elasticity to -0.0648. This result was unexpected. Inclusion of bed size or the ratio of full time physicians to beds as center attributes (Models 2, 3, and 4) does not change elasticity estimates appreciably. Use of miles rather than log miles (Model 5) also does not change the elasticity estimate.

The quality variable in Models 1-6 is based on outcomes for transplants occurring during the period in which patients registered. Since outcomes data for this period were not publicly available at the time of registration and in many cases had yet to actually occur (recall that the outcome is graft failure at one-year post transplant), this specification assumes that patients, physicians, and payers are very well informed. Alternative models were estimated where the quality variable is based on the latest center-specific outcome report available at the time of registration (reports were released annually up to September 2000 and biannually thereafter). For example, the outcome variables for patients registering in February 2002 are based on the outcome report released in January of 2002, and the outcome variables for patients registering in October 2002 are based on the July 2002 outcome report.

The sample elasticity from a model that includes quality (from the latest outcomes report card at registration), distance, and lagged market share as center attributes (Model 7) is -0.0347. Dropping lagged market share as a center attribute (Model 8) results in a much higher elasticity estimate, -0.0933, as expected.

One result that came through very strongly in all of the models was that the interaction of quality with private insurance was negative and significant, implying that privately insured patients are less likely to register at poor quality hospitals. Based on parameter estimates from Model 1, the sample elasticity if all patients in the sample were privately insured would be -0.200 (SE 0.0020). This finding is consistent with the claims of private insurers that their "centers of excellence" programs steer patients to high-quality centers (as discussed in Section 4). Further exploration of this result is left for future research.

7. Conclusion

This study adds to a growing body of research showing that patients take quality into account when choosing hospitals. Results indicate that an increase of one standard deviation in one-year graft failure rates is associated with a 2 to 5 percent decline in patient registrations, depending on the specification. Consistent with the findings of Escarce et al. (1999) and Chernew et al. (1998), privately insured patients are found to be particularly responsive to quality.

How generalizable are these results? Transplantation is undoubtedly a special case, but so are other procedure types (for example, cardiac surgery) that have been the subject of previous choice studies. There are reasons to expect that transplant patients are more responsive to quality than candidates for other procedures. For example, the consequence of poor quality is often death, and the cohesiveness of providers of care for end stage renal disease patients may facilitate the diffusion of quality information through informal channels. There are also reasons to expect that transplant patients are less responsive to quality; namely, many are very sick and poorly educated.

The implication of this study for transplant policy is that competition between transplant centers for patients can provide incentives to improve outcomes. An important caveat is that this study has not assessed transplant centers' strategic responses to competition. Competition may induce centers to invest in quality-improvement efforts. At the same time, competition may lead hospitals to "game" the organ allocation system to increase their allotment of organs (Scanlon et al. 2004). It may also decrease incentives for centers to invest in efforts to increase organ donation, since the gains must be shared with competitors. Evaluations of the impact of competition in transplantation must go beyond the standard economic framework to consider losses due to suboptimal use of the donor pool.

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Table 1: Summary of transplant center outcome measures, July 2003 report

	Mean	SD	Min	Max
Actual one-year graft failure rate	0.09	0.05	0.00	0.50
Expected one-year graft failure rate	0.09	0.01	0.05	0.16
Quality (Expected rate minus actual rate)	0.00	0.05	-0.11	0.37
Number of transplants 1/1/00-6/1/2002	155	133	1	932
N	206			

Table 2: Summary of transplant center attributes facing January 2000-October 2002 registrants

Variable	Mean	SD	Min	Max
Individual level, actual choices				
Quality, July 2003 report	0.00	0.03	-0.37	0.08
Distance in miles	38	51	0	1,261
Lagged market share	0.40	0.26	0.00	1.00
N	36,678			
Entire data set				
Quality, July 2003 report	0.00	0.04	-0.37	0.11
Distance in miles	65	109	0	1,434
Lagged market share	0.17	0.21	0.00	1.00
N	206,914			

Table 3: Summary of patient characteristics

White	47%
Age <65	86%
Diabetic	39%
On dialysis	82%
College degree	15%
Working	35%
Insurance	
Medicaid	7%
Private insurance	47%
Medicare/Other	46%
N	

Table 4: Patients' willingness to bypass nearby transplant centers for quality

Distance rank of centers in choice set	Center in choice set with best outcomes, number choosing (percent)						
	Closest	2nd closest	3rd closest	4th closest	5th closest	6th+ closest	Total
Closest	**3,321**	2,945	3,325	1,665	1,227	1,223	13,706
	(48%)	(35%)	(32%)	(34%)	(41%)	(40%)	(37%)
2nd closest	1,830	**4,008**	2,326	1,667	560	625	11,016
	(26%)	**(47%)**	(23%)	(34%)	(19%)	(21%)	(30%)
3rd closest	1,083	757	**3,803**	400	540	322	6,905
	(16%)	(9%)	**(37%)**	(8%)	(18%)	(11%)	(19%)
4th closest	316	436	298	**794**	197	101	2,142
	(5%)	(5%)	(3%)	**(16%)**	(7%)	(3%)	(6%)
5th closest	183	153	180	175	**230**	173	1,094
	(3%)	(2%)	(2%)	(4%)	**(8%)**	(6%)	(3%)
6th+ closest	206	177	323	268	263	**578**	1,815
	(3%)	(2%)	(3%)	(5%)	(9%)	**(19%)**	(5%)
Total	6,939	8,476	10,255	4,969	3,017	3,022	36,678

Table 5: Model estimates, January 2000-October 2002 registrants and July 2003 report

	Center attributes		
	Quality	Log distance	Lagged market share
	Mean parameters		
Level	0.120	-0.744 *	4.075 *
	(0.859)	(0.042)	(0.159)
×White	1.645 *	0.024	-0.668 *
	(0.406)	(0.021)	(0.077)
×Age<65	0.064	0.010	-0.512 *
	(0.615)	(0.029)	(0.109)
×Diabetic	-0.387	-0.009	0.352 *
	(0.393)	(0.020)	(0.077)
×On dialysis	-1.370 *	-0.038	-0.333 *
	(0.573)	(0.029)	(0.102)
×College degree	2.829 *	-0.031	-0.596 *
	(0.580)	(0.029)	(0.110)
×Working	0.194	-0.222 *	0.244 *
	(0.452)	(0.037)	(0.088)
×Insurance=Medicaid[a]	-1.946 *	-0.664 *	0.252
	(0.764)	(0.083)	(0.158)
×Insurance=Private[a]	3.742 *	0.209 *	0.827 *
	(0.440)	(0.030)	(0.108)
	Error components		
Level		0.044	5.124 *
		(0.026)	(0.308)
×Working		-1.151 *	
		(0.125)	
×On Medicaid		-1.767 *	
		(0.188)	
×Private insurance		0.825 *	-4.291 *
		(0.118)	(0.639)
Log-likelihood	43,409		
Psuedo R^2	0.260		

*P < 0.05

[a]Medicare and other insurance are omitted.

Standard errors are in parentheses.

Table 6: Quality-choice elasticity estimates

Model	Description	Quality-choice elasticity (SE)	Percent decline in registrations from a one standard deviation increase in graft failure rate
1	Center attributes: quality, distance, lagged market share	-0.0890 (0.0020)	-4.9%
2	Center attributes: quality, distance	-0.0648 (0.0023)	-3.6%
3	Center attributes: quality, distance, lagged market share, bed size	-0.0967 (0.0024)	-5.4%
4	Center attributes: quality, distance, bed size	-0.0656 (0.0022)	-3.6%
5	Center attributes: quality, distance, staff/bed ratio	-0.0601 (0.0021)	-3.3%
6	Same as model 1 but distance is miles instead of log miles	-0.0952 (0.0024)	-5.3%
7	Same as model 1 but quality is from latest report available at registration	-0.0347 (0.0027)	-1.9%
8	Same as model 2 but quality is from latest report available at registration	-0.0933 (0.0053)	-5.2%